AgMIP-Wheat multi-model simulations on climate change impact and adaptation for global wheat

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Abstract: The climate change impact and adaptation simulations from the Agricultural Model Intercomparison and Improvement Project (AgMIP) for wheat provide a unique dataset of multi-model ensemble simulations for 60 representative global locations covering all global wheat mega environments. The multi-model ensemble reported here has been thoroughly benchmarked against a large number of experimental data, including different locations, growing season temperatures, atmospheric CO_2 concentration, heat stress scenarios, and their interactions. In this paper, we describe the main characteristics of this global simulation dataset. Detailed cultivar, crop management, and soil datasets were compiled for all locations to drive 32 wheat growth models. The dataset consists of 30-year simulated data including 25 output variables for nine climate scenarios, including Baseline (1980-2010) with 360 or 550 ppm CO_2, Baseline +2ºC or +4ºC with 360 or 550 ppm CO_2, a mid-century climate change scenario (RCP8.5, 571 ppm CO_2), and 1.5°C (423 ppm CO_2) and 2.0ºC (487 ppm CO_2) warming above the pre-industrial period (HAPPI). This global simulation dataset can be used as a benchmark from a well-tested multi-model ensemble in future analyses of global wheat. Also, resource use efficiency (e.g., for radiation, water, and nitrogen use) and uncertainty analyses under different climate scenarios can be explored at different scales. The DOI for the dataset is 10.5281/zenodo.4027033 (AgMIP-Wheat, 2020), and all the data are available on the data repository of Zenodo (doi: 10.5281/zenodo.4027033). Two scientific publications have been published based on some of these data here.

Keywords: wheat, CO2, carbon dioxide, climate change, climate change scenario, multi-model ensemble, future crop yields, crop growth modeling.

1 BACKGROUND: As one of the largest staple crops, wheat (Triticum aestivum L.) plays an important role in ensuring global food security. Global wheat production, which covers tremendously diverse environments, is facing unprecedented climate change challenges (Lobell et al., 2011). Quantifying potential climate change impacts on global and regional crop production (including quantity and quality) accurately can provide valuable support for policy-making in mitigating climate change and for adapting local wheat production for future scenarios (IPCC, 2014).

Daily wheat development and growth dynamic at 60 global locations during a 30-year period were simulated as part of the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig et al., 2013) for wheat under different climate change scenarios with 32 wheat growth models. The multi-model ensemble reported here has been thoroughly benchmarked against a large number of experimental data, including different locations, growing season temperatures, atmospheric CO_2 concentration, heat stress scenarios, and their interactions (Asseng et al., 2015; Asseng et al., 2013; Asseng et al., 2019; Martre et al., 2015). The 60 global locations covered contrasting conditions across all global wheat mega environments and included 30 high-rainfall or irrigated wheat-growing locations and 30 low-rainfall wheat-growing locations (Reynolds and Braun, 2013). Each location represents an important wheat-growing area worldwide (Fig. 1). The climate scenarios considered here include Baseline (1980-2010) with a carbon dioxide concentration ([CO_2]) of 360 or 550 ppm, Baseline +2ºC or +4ºC with 360 or 550 ppm CO_2, 2050s under representative concentration pathway (RCP) 8.5, and 1.5ºC and 2.0ºC warming above the pre-industrial period from the Half a degree Additional warming, Prognosis and Projected Impacts project (referred to as 1.5ºC HAPPI and 2.0ºC HAPPI). These different climate scenarios represent different global warming levels (Ruane et al., 2017). Five global climate models (GCMs) were used to produce the future climate change scenarios to consider the uncertainty in climate projections in RCP8.5 and HAPPI scenarios. Instead of using regional-averaged model inputs, detailed cultivar, crop management, and soil datasets were compiled for the 60 locations. In addition, the effects of possible genetic adaptation with delayed anthesis date and increased potential grain filling rate were explored to quantify the impact of trait adaptation on global wheat production under baseline and RCP8.5.

2 METHODS: Following AgMIP protocols, all modelling teams who joined the AgMIP-Wheat activities were provided with the same modelling protocols. The protocols were developed by the AgMIP team to standardize all critical steps to configure the simulations of the modelling experiments. Each individual modelling group executed the full set of model simulations. The datasets of AgMIP-Wheat global simulations consists of the model outputs of 32 wheat models for 60 global wheat-producing locations under up to nine different climate scenarios. The protocol for running the global simulations under Baseline scenarios is provided as an example in the supplementary information.

2.1 Global locations: The 60 global locations were selected by two steps. In the AgMIP-Wheat Phase 2, simulations for 30 high rainfall / irrigated locations (Locations 1 to 30) were conducted. And, in the AgMIP-Wheat Phase 3, another 30 locations for rainfed/low input wheat regions (Locations 31 to 60) were added (Table S1). Each location within each mega environment was selected based on consultations with the global community of wheat crop modelers, to be representative and to have quality data available. The 30 high-rainfall or irrigated wheat-growing locations represent about 68% of current global wheat production and the 30 low-rainfall wheat-growing locations with wheat yields below 4 t DM ha^{-1} represent about 32% of current global wheat production (Reynolds and Braun, 2013). The

60 locations cover all major wheat-growing mega-environment types worldwide (Gbegbelegbe et al., 2017) (Fig. 1).

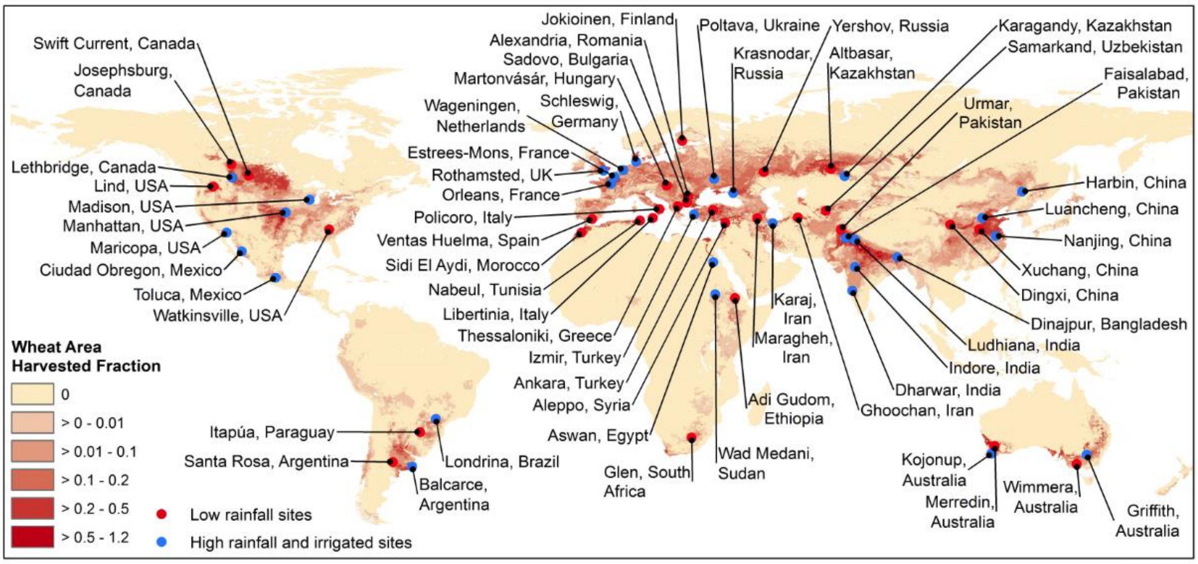

Figure 1. The thirty locations representing high rainfall and irrigated wheat regions (blue) and thirty locations representing low rainfall/low input regions (red) of the world used in the global simulations, after Asseng et al. (2019) and Liu et al. (2019). The thirty high rainfall and irrigated locations include locations which have low rainfall during the wheat growing season but have irrigation facilities. Wheat areas came from Monfreda et al. (2008)

2.2 Process-based wheat crop models: Table 1 lists the 32 wheat crop models used. Most of these models have been evaluated with detailed experiments (e.g., different growth locations, sowing dates, chronic warming, heat stress, FACE), and have been encouraged to improve their models in recent AgMIP simulation activities (Maiorano et al., 2017; Wang et al., 2017). All models can be downloaded on the Internet or requested from the corresponding person. For the two HAPPI scenarios, only 31 models participated in the global simulations, all 32 models were used in the simulations for the other climate scenarios.

Among the 32 models, the wheat models even with similar names, used here still have different model structures and parameters. For example, the 3 different Expert-N wheat models use different algorithms to simulate wheat growth and yield, even they have similar framework in simulating soil dynamics. According to our previous study (Wallach et al., 2018), it's currently hard to conclude which models would perform better, as different model performance were observed under different modelling experiments and conditions. Appling a multi-model ensemble approach by adding more models would decrease the uncertainty significantly (Martre et al., 2015).Therefore, the modelling results from the 32 models were reported here.

Table 1. List of the 32 wheat crop models used in the AgMIP Wheat study §

Code	Name (version)	Reference	Documentation
AE	APSIM-E*	(Chen et al., 2010; Keating et al., 2003; Wang et al., 2002)	http://www.apsim.info/Wiki
AF	AFRCWHEAT2*	(Porter, 1984; Porter, 1993; Weir et al., 1984)	Request from John Porter: jrp@plen.ku.dk
AQ	AQUACROP (V.4.0)	(Steduto et al., 2009)	http://www.fao.org/nr/water/aquacrop.html
AW	APSIM-Wheat (V.7.3)*	(Keating et al., 2003)	http://www.apsim.info/Wiki
CS	CropSyst (V.3.04.08)	(Stockle et al., 2003)	http://modeling.bsyse.wsu.edu/CS_Suite_4/CropSyst/index.html
DC	DSSAT-CERES-Wheat (V.4.0.1.0)*	(Jones et al., 2003; Ritchie et al., 1985; Ritchie et al., 1998)	http://dssat.net/
DN	DSSAT-Nwheat*	(Asseng, 2004; Kassie et al., 2016)	http://dssat.net/

Table 1. List of the 32 wheat crop models used in the AgMIP Wheat study (Continued) §

Code	Name (version)	Reference	Documentation
DR	DSSAT-CROPSIM (V4.5.1.013)*	(Hunt and Pararajasingham, 1995; Jones et al., 2003)	http://dssat.net/
DS	DAISY (V.5.24)*	(Hansen et al., 2012; Hansen et al., 1991)	http://daisy.ku.dk
EI	EPIC-I (V0810)	(Balkovič et al., 2013; Balkovič et al., 2014; Kiniry et al., 1995; Williams, 1995; Williams et al., 1989)	http://epicapex.tamu.edu/epic
EW	EPIC-Wheat(V1102)	(Izaurralde et al., 2012; Izaurralde et al., 2006; Kiniry et al., 1995; Williams, 1995; Williams et al., 1989)	http://epicapex.brc.tamus.edu
GL	GLAM (V.2 updated)	(Challinor et al., 2004; Li et al., 2010)	https://www.see.leeds.ac.uk/research/icas/research-themes/climate-change-and-impacts/climate-impacts/glam
HE	HERMES (V.4.26)*	(Kersebaum, 2007; Kersebaum, 2011)	https://www.zalf.de/en/forschung_lehre/software_downloads/Pages/default.aspx
IC	INFOCROP (V.1)	(Aggarwal et al., 2006)	https://www.iari.res.in/infoCrop_v2/InfoCrop-Registration.php
LI	LINTUL4 (V.1)	(Shibu et al., 2010; Spitters and Schapendonk, 1990)	http://models.pps.wur.nl/node/950
L5	SIMPLACE<Lintul-5* SlimWater3, FAO-56, CanopyT, HeatStressHourly	(Gaiser et al., 2013; Shibu et al., 2010; Spitters and Schapendonk, 1990; Webber et al., 2016)	http://www.simplace.net/Joomla/
LP	LPJmL (V3.2)	(Beringer et al., 2011; Bondeau et al., 2007; Fader et al., 2010; Gerten et al., 2004; Müller et al., 2007; Rost et al., 2008)	https://www.pik-potsdam.de/research/projects/activities/biosphere-water-modelling/lpjml
MC	MCWLA-Wheat (V.2.0)	(Tao et al., 2009a; Tao and Zhang, 2010; Tao and Zhang, 2013; Tao et al., 2009b)	Request from taofl@igsnrr.ac.cn
MO	MONICA (V.1.0)*	(Nendel et al., 2011)	http://monica.agrosystem-models.com
NC	Expert-N (V3.0.10) CERES (V2.0)*	(Biernath et al., 2011; Priesack et al., 2006; Ritchie et al., 1987)	https://expert-n.uni-hohenheim.de/en
NG	Expert-N (V3.0.10) GECROS (V1.0)*	(Biernath et al., 2011; Yin and van Laar, 2005)	https://expert-n.uni-hohenheim.de/en
NP	Expert-N (V3.0.10) SPASS (2.0)*	(Biernath et al., 2011; Priesack et al., 2006; Wang and Engel, 2000;)	https://expert-n.uni-hohenheim.de/en
NS	Expert-N (V3.0.10) SUCROS (V2)	(Biernath et al., 2011; Goudriaan and Van Laar, 1994; Priesack et al., 2006)	https://expert-n.uni-hohenheim.de/en
OL	OLEARY (V.8)*	(Latta and O'Leary, 2003; Maiorano et al., 2017; O'Leary and Connor, 1996a; O'Leary and Connor, 1996b; O'Leary et al., 1985)	Request from gjoleary@yahoo.com
S2	Sirius (V2014)*	(Jamieson and Semenov, 2000; Jamieson et al., 1998; Lawless et al., 2005; Semenov and Shewry, 2011)	https://sites.google.com/view/sirius-wheat/

Table 1. List of the 32 wheat crop models used in the AgMIP Wheat study (Continued) §

Code	Name (version)	Reference	Documentation
SA	SALUS (V.1.0)*	(Basso et al., 2010; Senthilkumar et al., 2009)	http://salusmodel.glg.msu.edu
SP	SIMPLACE<Lintul-2 CC,Heat,CanopyT,Re-Translocation	(Angulo et al., 2013)	http://www.simplace.net/Joomla/
SQ	*SiriusQuality* (V3.0)*	(Ferrise et al., 2010; He et al., 2010; Maiorano et al., 2017; Martre et al., 2006)	http://www1.clermont.inra.fr/siriusquality
SS	SSM-Wheat	(Soltani et al., 2013)	Request from afshin.soltani@gmail.com
ST	STICS (V.1.1)*	(Brisson et al., 2003; Brisson et al., 1998)	http://www6.paca.inra.fr/stics_eng
WG	WheatGrow (V3.1)	(Cao et al., 2002; Cao and Moss, 1997; Hu et al., 2004; Li et al., 2002; Pan et al., 2007; Pan et al., 2006; Yan et al., 2001)	Request from yanzhu@njau.edu.cn
WO	WOFOST (V.7.1)	(de Wit et al., 2020)	http://www.wofost.wur.nl

§ After Asseng et al. (2019) and Liu et al. (2019)

*Models that have routines to simulate crop and grain nitrogen dynamics leading to grain protein and have been tested with field measurements before. These 18 models have been used in the grain protein analysis.

2.3 Model inputs

2.3.1 Climate scenarios

Nine climate scenarios were considered, including Baseline (1980-2010) with 360 or 550 ppm [CO_2], Baseline +2°C or +4°C with 360 or 550 ppm [CO_2], 2050s climate projections under RCP8.5, and 1.5°C and 2.0°C warming above the 1861-1880 pre-industrial period from HAPPI, which correspond to ~ 0.6°C and 1.1°C above current global mean temperature (Table 2). Five GCMs were used to produce the future climate change scenarios in order to allow one to consider the uncertainty of climate projections for both the RCP8.5 and HAPPI scenarios.

The Baseline (1980-2010) climate data are from the AgMERRA climate dataset (Ruane et al., 2015a), which combines observations, data assimilation models, and satellite data products to provide daily maximum and minimum temperatures, solar radiation, precipitation, wind speed, vapor pressure, dew point temperatures, and relative humidity corresponding to the maximum temperature time of day for each location. These data correspond to 360 ppm [CO_2]. The Baseline+2°C and Baseline+4°C scenarios were created by adjusting each day's maximum and minimum temperatures upward by that amount and then adjusting vapor pressure and related parameters to maintain the original relative humidity at the maximum temperature time of day. Observations and projections of climate change indicate that relative humidity is relatively stable even as this implies increases in specific humidity as temperatures increase (commensurate with the Clausius-Clapeyron equation (Allen and Ingram, 2002). The values 360 and 550 ppm [CO_2] were used for the simulations in Baseline and Baseline+2°C and Baseline+4°C scenarios.

The RCP8.5 scenarios used here represents a relatively high emission scenario for the middle of the 21st century (RCP8.5 for 2040-2069, 571 ppm [CO2] in 2055). Projections for RCP8.5 were taken from five GCMs that are representative of the CMIP5 multi-climate model ensemble (HadGEM2-ES, MIROC5, MPI-ESM-MR, GFDL-CM3, GISS-E2-R) (Ruane and McDermid, 2017), with historical conditions modified to reflect projected changes in mean temperatures and precipitation along with shifts in the standard deviation of daily temperatures and the number of rainy days. These scenarios were created using the "Enhanced Delta Method" (Ruane et al., 2015b), and GCMs were selected to include models with relatively large and relatively small global sensitivity to the greenhouse gases that drive climate changes to account for the uncertainty of the fifth coupled model intercomparison project (CMIP5) GCMs ensemble (Ruane and McDermid, 2017). Solar radiation changes from GCMs introduce uncertainties that can at times overwhelm the impact of temperature and rainfall changes. Therefore, as in previous AgMIP assessments, changes in solar radiation were not considered here other than small radiation effects associated with changes in the number of precipitation days (Ruane et al., 2015b).

The 1.5°C and 2.0°C HAPPI scenarios here are consistent with the AgMIP Coordinated Global and Regional Assessments (CGRA) 1.5 and 2.0°C World Study (Rosenzweig et al., 2016; Ruane et al., 2018), using the methods fully described by Ruane et al. (2018). In brief, climate changes from large (83-500 members for each model) climate model ensemble projections of the +1.5 and +2.0°C scenarios from HAPPI (Mitchell et al., 2017) were combined with the local AgMERRA baseline to generate driving climate scenarios from five GCMs (MIROC5, NorESM1-M, CanAM4 [HAPPI], CAM4-2degree [HAPPI], and HadAM3P) for each location (Ruane et al., 2018). Specifically, the HAPPI ensemble changes in monthly mean climate, the number of precipitation days, and the standard deviation of daily maximum and minimum temperatures were imposed upon the historical AgMERRA daily series using quantile mapping that forces the observed conditions to mimic the future distribution of daily events (Ruane et al., 2018; Ruane et al., 2015b). This results in climate scenarios that maintain the characteristics of local climate while also capturing major climate changes. HAPPI anticipates [CO2] for the 1.5°C and 2.0°C scenarios of 423 and 487 ppm, respectively. As the HAPPI project (www.happimip.org/) was designed specifically to represent a stable climate in a +1.5 and +2.0 world, not for a specific time period. Therefore, there is no indication for the time period for scenarios 18-27 in Table 2.

Table 2 Outline of the baseline and climate change scenarios considered in the global simulations [§]

Scenario id	Period	Climate scenario		Global Climate model		CO_2		Adaptation	
	Years	Name	Code	Name	Code	ppm	Code	Name	Code
01	1981-2010	Baseline	B0	-	0	360	C360	None	N
02	1981-2010	Baseline	B0	-	0	360	C360	2-traits combination	T
03	1981-2010	Baseline+2°C	B2	-	0	360	C360	None	N
04	1981-2010	Baseline+4°C	B4	-	0	360	C360	None	N
05	1981-2010	Baseline	B0	-	0	550	C550	None	N
06	1981-2010	Baseline+2°C	B2	-	0	550	C550	None	N
07	1981-2010	Baseline+4°C	B4	-	0	550	C550	None	N
08	2040-2069	RCP8.5	85	HadGEM2-ES	K	571	C571	None	N
09	2040-2069	RCP8.5	85	MIROC5	O	571	C571	None	N
10	2040-2069	RCP8.5	85	MPI-ESM-MR	R	571	C571	None	N
11	2040-2069	RCP8.5	85	GFDL-CM3	1	571	C571	None	N
12	2040-2069	RCP8.5	85	GISS-E2-R	2	571	C571	None	N
13	2040-2069	RCP8.5	85	HadGEM2-ES	K	571	C571	2-traits combination	T
14	2040-2069	RCP8.5	85	MIROC5	O	571	C571	2-traits combination	T
15	2040-2069	RCP8.5	85	MPI-ESM-MR	R	571	C571	2-traits combination	T
16	2040-2069	RCP8.5	85	GFDL-CM3	1	571	C571	2-traits combination	T
17	2040-2069	RCP8.5	85	GISS-E2-R	2	571	C571	2-traits combination	T
18	-	1.5°C HAPPI	15	NorESM1-M	T	423	C423	None	N
19	-	1.5°C HAPPI	15	MIROC5	O	423	C423	None	N
20	-	1.5°C HAPPI	15	CanAM4	4	423	C423	None	N
21	-	1.5°C HAPPI	15	CAM4-2degree	5	423	C423	None	N
22	-	1.5°C HAPPI	15	HadAM3P	8	423	C423	None	N
23	-	2.0°C HAPPI	20	NorESM1-M	T	487	C487	None	N
24	-	2.0°C HAPPI	20	MIROC5	O	487	C487	None	N
25	-	2.0°C HAPPI	20	CanAM4	4	487	C487	None	N
26	-	2.0°C HAPPI	20	CAM4-2degree	5	487	C487	None	N
27	-	2.0°C HAPPI	20	HadAM3P	8	487	C487	None	N

[§] After Asseng et al. (2019) and Liu et al. (2019)

2.3.2 Soil: Locations 1 to 30 were simulated using soil information from Maricopa, USA (location 1), as no water or N limitations were considered (Table S1). Soil information for locations 31 to 60 were obtained from a global soil database (Romero et al., 2012). The soil closest to a location was used, but for locations 39 and 59, soil carbon was decreased after consulting local experts. Initial soil nitrogen was set to 25 kg N ha^{-1} NO_3-N and 5 kg N ha^{-1} NH_4-N per 100 cm soil depth and reset each year for locations 31 to 60. Initial plant available soil water for spring wheat sown after winter at locations 31 to

60 was set to 100 mm, starting from 10 cm depth until 100 mm was filled in between drained lower limit (LL) and drained upper limit (DUL). The first 10 cm were kept at LL and reset each year. If wheat was sown after summer, initial plant available soil water was set to 50 mm, starting from 10 cm depth until 50 mm was filled in between LL and DUL. The first 10 cm were kept at LL and reset each year. The details of soil for all 60 locations can be found in data archive. In general, the soil data used for locations 31-60 were representative for the selected mega environment, as local experts were consulted when compiling the soil data.

2.3.3 Crop management: For locations 1 to 30 sowing dates were fixed at a specific date. For locations 31 to 60, sowing windows were defined and a sowing rule was used. The sowing window was based on sowing dates reported in literature. For locations 41, 43, 46, 53, 54, and 59, sowing dates were not reported in literature and estimates from a global cropping calendar were used (Portmann et al., 2010). The cropping calendar provided a month (the 15th of the month was used) in which wheat is usually sown in the region of the location. The start of the sowing window was the reported sowing date and the end of the sowing window was set two months later. Sowing was triggered in the simulations on the day after cumulative rainfall reached or exceeds 10 mm over a 5-day period during the predefined sowing window. Rainfall from up to 5 days before the start of the sowing window was considered. If these criteria were not met by the end of the sowing window, wheat was sown on the last day of the sowing window. Sowing dates were left unchanged for future scenarios.
Locations 1 to 30 were simulated without N or water limitation, therefore no inputs for crop water and N management were supplied. No irrigation was applied for the 30 low-rainfall wheat-growing locations. For locations 31 to 60, fertilizer rates were determined based on a FAO database (FAO, 2013) and expert knowledge, which can be found in Gbegbelegbe et al. (2017). Fertilizer rates were set low (20 to 50 kg N ha^{-1}) at locations 31, 32, 48, 51, 53, and 60; medium (60 kg N ha^{-1}) at locations 33 to 43, 45 to 47, 49, 50, 52, 54, and 57 to 59; and relatively high (100 to 120 kg N ha^{-1}) at locations 44, 55, and 56. All fertilizer was applied at sowing.

2.3.4 Cultivars: To carry out the global impact assessment and exclusively focus on climate change, region-specific cultivars were used in all 60 locations. Detailed information were available on cultivars grown in locations 1 to 30, whereas they were only limited in locations 31 to 60. Therefore, in these sites cultivar characteristics were defined by selecting the most presumably suitable cultivars from the first set of locations. Observed local mean sowing, anthesis, and maturity dates were supplied to modelers with qualitative information on vernalization requirements and photoperiod sensitivity for each cultivar (Table S1).
For locations 35, 39, 47, 49, and 55 to 57 (Table S1), anthesis dates were reported in the literature. For the remaining sites from 31 to 60, anthesis dates were estimated with the APSIM-Wheat model. Maturity dates were estimated from a cropping calendar for sites 31, 32, 37, 38, 41 to 46, 49 to 54, and 58 to 59 (Table S1) where no information from literature was available. For locations 31 to 60, observed grain yields from the literature (Table S1) were provided to modelers with the aim to set up wheat models to have similar yield levels, as well as similar anthesis and maturity dates. No yields were reported for sites 49 and 56, so APSIM-Wheat yields were estimated and used as a guide.

2.3.5 Cultivar adaptation: The RCP8.5 scenario and Baseline were examined with current management as well as under one possible trait adaptation, which is a cultivar combining delayed anthesis and an increased potential grain filling rate.
To consider the diversity of model approaches of the 32 participating wheat models and allow all modelers to incorporate the trait adaptations in their models, we proposed a simple but yet physiologically sound trait combination. The proposed traits were simulated in full combination only, to quantify the impact of such a trait combination. The aim of these simulations was not to analyze the contribution of various individual traits, nor to explore the full range of traits that could possibly assist in an adaptation strategy. The proposed simple trait combination that aimed to minimize the impact of future increased temperatures on global yield production included:
1. *Delayed anthesis by about 2 weeks under the Baseline* scenario via increased temperature sum requirement, photoperiod sensitivity, or vernalization requirement. No change in the temperature requirement for grain filling duration was considered.
2. *Increased rate (in amount per day) of potential grain filling by 20%* (escape strategy).
It should be noted that this trait combination is currently available in wheat breeding lines and was shown to be associated with significant yield increases in warm environments (Asseng et al., 2019).

2.4 Model configuration

Before conducting global simulations, modelers were asked to use the supplied sowing dates and calibrate their cultivar parameters against the observed anthesis and maturity dates by considering the qualitative information on vernalization requirements and photoperiod sensitivity. In the global simulations for locations 1 to 30, no water or nitrogen stress was considered.

The trait adaptation was simulated by adjusting the cultivar parameters for each location (Table S2). In 30 of the 32 models, anthesis date was delayed by increasing the thermal time requirement between emergence and anthesis, and for five models also by increasing the vernalization requirement and/or the photoperiod sensitivity. In two models (AE and DN) anthesis date was delayed without changing the thermal time requirement.

For the adaptation of grain filling trait, the 32 models were classified into five group according to how models implemented the adaptation to increase grain filling rate.

Group 1: Sixteen models with increased rate of grain filling (or harvest index change), including AE, AF, AW, DN, EW, IC, LI, NC, NP, NS, OL, SA, GL, MC, SS, ST, WG;

Group 2: Five models with increased potential grain size (or final harvest index), including DC, DR, CS, EI, and LP;

Group 3: Two models with increased fraction of vegetative biomass remobilization, including L5 and SP;

Group 4: One model with decreased grain filling duration (AQ);

Group 5: Seven models with no parameter change to increase the rate of grain filling, including DS, HE, MO, NG, S2, SQ, and WO.

Table 2 shows the combination of climate scenarios, CO_2 concentration, and trait adaptation for all 27 scenarios.

2.5 Model outputs: Table 3 shows the 25 output variables from each model that were requested. Output data for 30 growing seasons under the same scenario were bind into the same text file as 30 line records. Results for variables that some models do not simulate are indicated with “na”.

Table 3. Definitions of model output variables

Variable	Unit	Definition
Model	-	2-letter model code
Year	YYYY	Year of harvest
Yield	Mg DM ha^{-1}	Final grain yield at 0% moisture
Sowing	YYYY-MM-DD	Sowing date
Emergence	YYYY-MM-DD	Crop emergence date - Zadoks 10
Anthesis	YYYY-MM-DD	Anthesis date - Zadoks 65
Maturity	YYYY-MM-DD	Physiological maturity date - Zadoks 89
GNumber	grain m^{-2}	Grain number per unit ground area
Haun	Leaf mainstem^{-1}	Decimal number of emerged leaves per main stem (Haun index)
Biom-an	Mg DM ha^{-1}	Cumulative total above ground dry biomass at anthesis
Biom-ma	Mg DM ha^{-1}	Cumulative total above ground biomass at physiological maturity (including grain)
MaxLAI	m^2 m^{-2}	Maximum leaf area index (green)
WDrain	mm	Cumulative (sowing to maturity) water drained below 150 cm at physiological maturity
CumET	mm	Cumulative evapotranspiration (sowing to maturity) at physiological maturity
SoilAvW	mm	Plant available soil water content (soil water minus plant lower limit) in soil profile (0-150 cm) at physiological maturity [a]
Runoff	mm	Cumulative runoff at physiological maturity
Transp	mm	Cumulative crop transpiration (sowing to maturity) at physiological maturity
CroN-an	kg N ha^{-1}	Cumulative total above ground N mass (crop N uptake) at anthesis
CroN-ma	kg N ha^{-1}	Cumulative total above ground N mass (crop N uptake including grain) at physiological maturity
Nleac	kg N ha^{-1}	Cumulative soil N leached (sowing to physiological maturity) below 150 cm at physiological maturity [a]
GrainN	kg N ha^{-1}	Grain N mass at physiological maturity
Nmin	kg N ha^{-1}	Cumulative N mineralization (sowing to physiological maturity) in soil profile (0-150 cm) at physiological maturity [a]

Table 3. Definitions of model output variables (Continued)

Variable	Unit	Definition
Nvol	kg N ha^{-1}	Cumulative soil N volatilization (sowing to physiological maturity) at physiological maturity
Nimmo	kg N ha^{-1}	Cumulative soil N immobilization (sowing to physiological maturity) in soil profile (0-150 cm) at physiological maturity [a]
SoilN	kg N ha^{-1}	Inorganic soil N (NO3-N + NH4-N) in soil profile (0-150 cm) at physiological maturity [a]
Nden	kg N ha^{-1}	Cumulative soil N denitrification (sowing to physiological maturity) in soil profile (0-150 cm) at physiological maturity [a]
ETo	mm	Cumulative potential evapotranspiration (sowing to physiological maturity) at physiological maturity
GPC	%	Grain protein concentration

[a] For locations with root depth less than 150 cm, only the soil available water content or nitrogen variables from root growth layers was reported.

3 DATA RECORDS

3.1 Data format: Data are provided in 27 “TAB” limited text files. Each file contains all annual output variables for all 30 growing seasons from the 32 (scenarios 1 to 17 in Table 2) or 31 (scenarios 18 to 27 in Table 2) wheat models for the 60 global locations in one scenario combination. Files are named following the convention below:
[Scenario id]-[Climate scenario]-[GCM]-[CO_2]-[Adaptation].txt

In the data archive (AgMIP-Wheat, 2020), codes for the scenario id, climate scenario, GCM, CO_2 and adaptation in the file name are given in Table 2. In each text file, the 2-Letter model code is the abbreviation for crop models in Table 1, location number is the two-digits number from Table S1, and definitions of other output variables are given in Table 3. In the simulation output files, the years were kept to 1981-2010 in the future climate scenarios, instead of using the time periods in Table 2. This was simply because the future climate data were developed based on baseline (1980-2010) climate date, and the years in the future climate were left unchanged.

3.2 Data availability: The DOI for the dataset is 10.5281/zenodo.4027033 (AgMIP-Wheat, 2020). Data are available on the data repository of Zenodo (http://doi.org/10.5281/zenodo.4027033). All global simulation data are published under the Creative Commons Attribution 4.0 International (CC BY 4.0) license.

3.3 Technical Validation: All global simulation data submitted to the AgMIP-Wheat team were tested by using a custom made R script for quality checking. Data were tested for compliance with data formats, checking units, variable naming, and file naming. Errors in data formatting, data ranges, and time coverage were reported to modelling groups, so that they could check and fix the simulation data.

3.4 Code Availability: The data of the AgMIP-Wheat global simulation dataset were produced by the individual modelling groups using different wheat crop models. The source code of these models is subject to different distribution policies and needs to be requested from the individual groups.

4 SUMMARY: The primary idea of these global simulations was to quantify global impacts on wheat production under different climate change scenarios. Local climate change impacts on wheat grain yield and protein (only for RCP8.5) were aggregated to global scale with a multi-model ensemble approach (Asseng et al., 2019; Liu et al., 2019). The simulated yields and protein can be used as a benchmark from a well-tested multi-model ensemble in future analyses. The multi-model outputs provide a comprehensive dataset for investigating resource use efficiency (e.g., for radiation, water, and nitrogen use) under different climate scenarios proposed recently (Porter et al., 2019). Also, the dataset can be used to explore how to increase different resource use efficiencies while maintaining high yield and grain quality for different global wheat cropping systems in the future (Porter et al., 2019). Another potential use of this global simulation dataset is for uncertainty analysis, including comparison of different modelling approaches at different scales, different sources of uncertainties, and inter-annual variability.
As these datasets were developed mostly for assessing future temperature and CO_2 impacts on wheat production, several adaptation measures (e.g., changing sowing dates, improving fertilisation) were not considered. However, sowing dates would change due the changing rainfall patterns in future climate

scenarios, especially for low rainfall locations. This could limit the use of these simulations to explore climate change impact for these environments. Improving fertilisation, which could also increase wheat production for adapting to climate change, was not considered in the current datasets. Therefore, exploring the wheat yield increase potential by improving fertilisation at global scale should be considered in the next AgMIP-Wheat activities.

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